Link travel time estimation in urban areas by detectors and probe vehicles fusion

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ABSTRACT

This paper presents an approach to estimate link travel time in urban areas. This approach consists of a data fusion from underground loop detectors and probe vehicles equipped with global positioning system (GPS). This method is expected to be more accurate, reliable and robust than using either of these data sources alone. In this approach, an algorithm is developed. This algorithm is based on the unscented Kalman filter using vehicle counts and flows from loop detectors located at the end of every link, and travel time from probe vehicles. From these counts the average travel time is calculated using the "cumulative plot" method. Furthermore, in order to incorporate the GPS data, a map-matching method is used to associate a travel time to the appropriate link.

Keywords: *unscented Kalman filter, loop detector, probe vehicle, map-matching, travel time estimation*

INTRODUCTION

Travel time is the time required to traverse a route between any two points of interest. This information is an important parameter that can be used to identify and assess operational problems as well to measure the effectiveness of transportation systems. Travel times in excess (delay) causes indirect costs to drivers in terms of lost time, discomfort and frustration, and a direct cost in terms of fuel consumption. An excessive delay reflects the inefficiency of the system performance. Travel time information is easy to be perceived by users and has the potential to reduce congestion on both temporal and spatial scales. By reducing congestion, it provides traffic flow that reduces vehicle emissions and energy consumption, global warning and greenhouse effect. As a result, it maximizes the efficiency and capacity of the road network.

Travel time estimation has been an important research topic for decades. But most of these research estimate travel time for arterial/freeway areas.

Different techniques are used to estimate the travel time on roads. These techniques depend on the type of system used to collect traffic data. These systems may rely on traditional methods such as loop detectors [1], or advanced methods such as vehicle tracking devices by GPS or driver mobile phone (called probe vehicle) [2]. The traffic data obtained from magnetic loops provide information adjacent to where the detectors are installed (point measurement) while data from probe vehicles provide information describing the vehicle behavior. Thus, the traffic information obtained from a point measurement must be carefully used to estimate the spatial behavior of traffic. Similarly, information obtained from a vehicle sensor must be carefully used to estimate the behavior of all vehicles traversing.

However, both of them have some inherent flaws. For loop detectors, one major critic on the data is the high probability of error, for instance, due to equipment failure. Thus, it is necessary to verify the accuracy of data collected by loop detectors before the data can be used. For probe vehicles, the two main drawbacks are poor statistical representation and errors in the map-matching process.

The properties of these two data sources are complementary and redundant. Hence, they can be harnessed by developing a solution to merge multi-sensor data for the problem of estimating travel time in urban areas.

In this context, several methods have been presented in order to estimate the travel time in urban areas using the fusion of these multi-sources data. El Faouzi and Lefevre [3] employ evidence theory (ET), which is a strong tool when dealing with incomplete or inaccurate information. Qing-Jie Kong and al. [4] integrate the federated Kalman filter and ET, which has brought more advantages to the real-time fusion of heterogeneous traffic information. However, these methods have not dealt with traffic signals, which affect link travel time of probe vehicles, neither with the flow between links and their neighbors (as a congested link has direct effects on its neighboring links). Ashish Bhaskar [5, 6] in his thesis answered to these problems by estimating the cumulative number of vehicles plots on the upstream and downstream of a link. These numbers (or cumulative plots) are deterministically corrected by adding the data from the probe vehicles. This method is based on a hypothesis that errors in the map-matching process are null.

While some research investigations use loop detectors and probe vehicles, others use wireless magnetic sensors. The system of Kwong and al. [7] relies on these sensors that provide time when a vehicle passes by the sensors. Therefore a re-identification of the vehicle signature at two locations gives the corresponding travel time of this vehicle. Although this method is quite interesting, it requires some advanced type of sensors not yet so commonly used as loop detectors.

In order to estimate the travel time in urban areas, we propose the unscented Kalman filter. One important drawback of the Kalman filter is its limitation to a linear assumption. However, the process model or the observation model or both can be nonlinear. One can use the extended Kalman filter (EKF) instead of the Kalman filter, but unfortunately, the most important handicap of the EKF is the derivation of the Jacobian matrices, which for complex functions can be a difficult task in itself. In order to over-come the drawbacks of the EKF, the unscented Kalman filter (UKF) can be a suitable replacement for the EKF. Using the UKF, we remove the requirement to explicitly calculate Jacobian matrices, and in result this filter captures more accurately the true mean and covariance.

In this article we will use the UKF to estimate link travel time in urban areas. This paper is organized as follows: the cumulative plot method is drawn in the first paragraph. The second paragraph proposes a link travel time estimation method. The third paragraph explains briefly the UKF.

CUMULATIVE PLOT FOR TRAVEL TIME ESTIMATION

The cumulative plot is the graph of the cumulative number of vehicles passing by an observer (or detector) in a given place over time t from an arbitrary initial number. The points obtained are discrete because in practice the sensors are read every 1 minute (or 6 minutes) (there is no moment of passage of all vehicles...). These points must be interpolated and it is not trivial: this will be discussed later on in this section.

The cumulative function is monotonically increasing and we can assume it is differentiable with respect to time. The slope of the curve at time t is the instant flow of traffic at time t. The value of the cumulative function at time t is CP (t). This flow is equal to:

$$\left(CP\left(t+\Delta t\right)-CP\left(t\right)\right)\Big/\Delta t \ . \qquad (1)$$

Assuming that:

a) First-In-First-Out (FIFO) discipline is respected for all vehicles passing through upstream (u/s) and downstream (d/s) (no overtaking vehicle);

b) Vehicles are kept (for example, there is no loss or gain of vehicles in the segment);

Bhaskar interpolates between measurements applying a flow model that propagates counter values from one link to the next with the assumption of free flow. Hence, the interpolation for link k depends on that made previously for link k-1.

Fig.1 (from [5, 6]) describes two cumulative curves U(t) and D(t) obtained respectively in the scene (u/s) and (d/s) of a given link.

The vertical distance (along the Y axis) between the two curves at time t defines the instant counting gap (n) between the two locations. The horizontal distance (along the X axis) for the counter i that defines the travel time (TTi) for the *ith* vehicle. When a probe vehicle is available on a link at d/s, Bhaskar suggests a deterministic correction of the u/s cumulative plot that fits the instantaneous TTi measured. The estimated average travel time is defined by the total time for all vehicles N for the range of estimates of travel time (T_{EI}) (from the location d/s), i.e. the area (A) between the two cumulative curves. The average travel time per vehicle is the ratio A/N. We suggest a stochastic correction of the cumulative plot, which has led to the formulation discussed in next section.

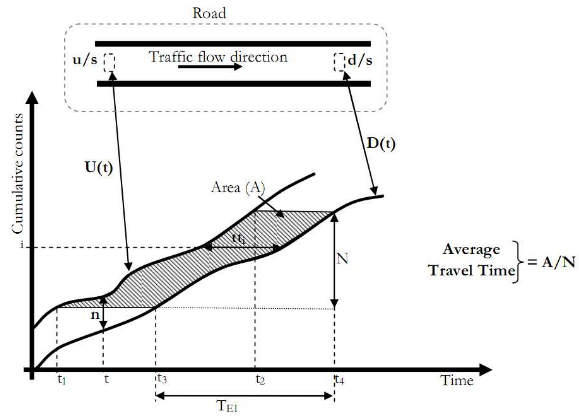

Fig. 1: Cumulative counts at upstream and downstream of an urban link

TRAVEL TIME ESTIMATION

Accurate travel time estimation is an important element for advanced traveler information systems and advanced traffic management systems as well for all transport users. In urban networks, travel time estimation is challenging due to many reasons such as the fluctuations in traffic flow due to traffic signals.

The traffic data from probe vehicles and loop detectors sources have different levels of accuracy, which may result in inconsistency and sometimes even contradictory estimates. Data fusion is the processing tool that takes into account the quality of the data provided by each source with the aim of increasing the accuracy, reliability and robustness of the estimation. While this method is an extension to Bhaskar’s one, it highlights the errors from both sources of data, i.e. loop detectors as well as probe vehicles considered null by Bhaskar’s modeling. Therefore, we propose a filter that fuses the data from probe vehicles and from detectors: we present the process model that we would like to use in order to achieve this operation.

We assume we have only one lane (in a more complete modeling, we will assume no lane change and one detector per lane). Therefore, the First in First out (FIFO) model applies, i.e. the overtaking on the road network is neglected. Moreover, we consider that each link is correlated with it neighbors links.

<u>State vector</u>

Suppose that we have a loop detector at the end of each link, and that we would like to estimate the travel time of link k at time t. The state vector contains:

- the travel time TT: this TT is an important element in order to be able to find $q_u(t-TT)$ for state evolution

- the cumulative count of vehicles at the downstream of link N_d
- the flow at the downstream of link q_d
- the cumulative count of vehicles at the upstream of link N_u
- the history of the flow at the upstream of the link k: q_u, which is also the flow at the downstream of the link k-1. This history tabulates a fixed number n of past flows, this number being an a priori parameter of our modeling.

Therefore the state vector resumes as follows:

$$x(t) = \begin{bmatrix} TT(t) \\ N_d(t) \\ q_d(t) \\ N_u(t) \\ q_u(t) \\ q_u(t - T_S) \\ .... \\ q_u(t - n \times T_S) \end{bmatrix}$$

Evolution

We suppose that state at time t evolves around the state at time t-T_S (typically at T_S = 1 second sample time) as follows:

- The travel time at time t is equal to the travel time at time t-T_S;
- The cumulative number at the downstream at time t is the cumulative number at the downstream at time t-T_S plus the flow at the downstream multiplied by the sample time;
- The flow at the downstream at time t is the flow at the upstream (i.e. at the downstream of link k-1) at time t-TT (this is actually the flow model through link k): TT/T_S is rounded to the nearest integer;
- The cumulative number at the upstream at time t is the cumulative number at the upstream at time t-T_S plus the flow at the downstream multiplied by T_S;
- The flow at the upstream at time t is the flow at time t-T_S.

To resume the evolution of the state vector is as follows:

$$x_{t+T_S} = Fx_t + w_t \qquad (2)$$

where:

- w_t is the process noise assumed to be drawn from a zero mean normal distribution with covariance Q_t
- F is the state transition model applied to previous state x_t .

$$\begin{array}{cccccccccc}
 & TT(t) & N_d(t) & q_d(t) & N_u(t) & q_u(t) & q_u(t-T_S)... & q_u(t-TT)... & & q_u(t-n \times T_S) \\
F = & \left(\begin{matrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ ..... \\ 0 \end{matrix}\right. & \begin{matrix} 0 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ \\ 0 \end{matrix} & \begin{matrix} 0 \\ T_S \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ \\ 0 \end{matrix} & \begin{matrix} 0 \\ 0 \\ 0 \\ 1 \\ 0 \\ 0 \\ 0 \\ \\ 0 \end{matrix} & \begin{matrix} 0 \\ 0 \\ 0 \\ T_S \\ 1 \\ 1 \\ 0 \\ \\ 0 \end{matrix} & \begin{matrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 1 \\ \\ 0 \end{matrix} & \begin{matrix} \\ \\ 1 \\ \\ \\ \\ \\ \\ \\ \end{matrix} & \begin{matrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ \\ 1 \end{matrix} & \left.\begin{matrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ \\ 0 \end{matrix}\right)
\end{array}$$

We can notice that F contains a Jordan matrix in the lower right bloc. Moreover, the key point in this evolution model is that it depends on the state vector itself (the 1 at lane 3 is placed at column t-TT), which justifies the use of an UKF. The problem of quantification (i.e. the rounding of TT/T_S) will be properly addressed by the UKF.

Observations

Our observations are the travel time from probe vehicles and the number of vehicles as well as the occupancy from loop detectors. The observation of travel time from probe vehicles is obtained by a map-matching method. The data from the GPS probe vehicles contain vehicle ID, position coordinates, time, and eventually velocity, moving direction, etc. To estimate the travel time a map-matching process need to be made. This is the most important step in the estimating process; its accuracy will directly affect the final results. Map-matching algorithms generally adopt either a geometric or a probability statistical approach. For further detail refer to [8].

Therefore, at time t an observation or measurement z_t of the true state x_t is either:

Case 1: probe vehicle TT or loop counter:

$$z_t = Hx_t + v_t \quad \text{(linear model)} \qquad (3)$$

where:

- H is the observation model. In our case this model is: for TT (probe vehicles): $[1 \ \ 0 \ \ 0 \ \ 0 \ \ ... \ \ 0]$ for respectively d/s or u/s counters: $[0 \ \ 1 \ \ 0 \ \ 0 \ \ ... \ \ 0]$ or $[0 \ \ 0 \ \ 0 \ \ 1 \ \ ... \ \ 0]$
- v_t is the observation noise assumed to be zero mean Gaussian white noise with covariance R_t . This covariance is obviously different whether one considers TT or counters. As for TT, it should characterize possible errors in the process of map-matching GPS position. GPS errors, and the consecutive map-matching errors, will be fixed depending on the location of the link: in a dense city center, the order of magnitude of those errors is some tens of meters, whereas in an open area, it is only a few meters. In a very first approximation, we will classify links that way: city center / open area, fixing travel time observation errors to a maximum of 10 seconds down to few seconds.

Case 2: loop occupancy:

$$z_t = h(x_t) + v_t \quad \text{(nonlinear model)} \qquad (4)$$

where the observation model h is the following equation:

$$\frac{O}{L} = \frac{TT}{L_k} q \qquad (5)$$

with O being the occupancy, L sum of vehicle length (assumed to be a fix value of 5m) and the loop detector length and L_k length of the link k.

UNSCENTED KALMAN FILTER

The Kalman filter is a statistical approach used to estimate the state of a system from a priori information on the evolution of this state (model) and on the actual measurements. The basic Kalman filter is limited to a linear assumption. The most common way of applying the KF to a nonlinear system is in the form of the extended Kalman filter (EKF). Unfortunately, the most important drawback of the EKF is the derivation of the Jacobian matrices. In the EKF, the probability distribution function is propagated through a linear approximation of the system around the operating point at each instant of time. In doing so, the EKF needs the Jacobian matrices. However, this matrix can be sometimes difficult and complicated to obtain. Further, the linear approximation of the system at a given time instant may introduce errors in the state, which may lead the state to diverge over time. In other words, the linear approximation may not be appropriate for some systems. In order to overcome the drawbacks of the EKF, other nonlinear state estimators have been developed such as the unscented Kalman filter (UKF). The unscented Kalman filter (UKF) uses a deterministic sampling technique known as the unscented transform to pick a minimal set of sample points (called sigma points) around the mean. These sigma points are then propagated through the non-linear functions, from which the mean and covariance of the estimate are then recovered. In addition, this technique removes the requirement to explicitly calculate Jacobian matrices, which for complex functions can be a difficult task in itself. More details can be found in [9] & [10].

Given the state vector at step t, we compute a collection of sigma point, stored in the columns of the $L \times (2L+1)$ sigma point matrix x_t where L is the dimension of the state vector. The columns of x_t are computed and weighted by:

$$(x_t)_0 = \hat{x}_t \tag{6}$$

$$(x_t)_i = \hat{x}_t + \left(\sqrt{(L+\lambda)P_t}\right)_i, i = 1....L \tag{7}$$

$$(x_t)_i = \hat{x}_t - \left(\sqrt{(L+\lambda)P_t}\right)_{i-L}, i = L+1....2L \tag{8}$$

where $\left(\sqrt{(L+\lambda)P_t}\right)_i$ is the *ith* column of the matrix square root, λ is a parameter to determine, and P_t is the a posteriori estimate of the error covariance.

After the generation of the sigma points (eq. (7) and (8)), the transformed set is given by instantiating each point through the process model: $(\xi_t^-)_i = f\left((x_t^-)_i\right)$ (9)

The step that follows is to initiate each of the prediction points through observation model:

$$(z_t^-)_i = h\left((\xi_t^-)_i\right) \tag{10}$$

Finally, we update the filter using the Kalman gain K_t:

$$K_t = P_{xz} P_{yy}^{-1} \tag{11}$$

$$\hat{x}_t = \hat{x}_t^- + K_t\left(z_t - \hat{z}_t^-\right) \tag{12}$$

$$P_t = P_t^- - K_t P_{yy} K_k^T \tag{13}$$

where P_{xz} and P_{yy} are respectively the cross covariance and the innovation covariance, both computed from the updated sigma points.

CONCLUSION

The unscented Kalman filter uses an underlying process model to make an estimate of the current state of a nonlinear system and then corrects the estimate using any available sensor measurements. In addition to the reasons mentioned in the previous section, the choice of a filter to estimate the link travel time in urban areas lays on the UKF since the evolution model here depends on the state vector itself. Using this filter we have the possibility to introduce the error due to the map-matching process as well as the loop detectors, and the flow model through the studied link.

The next step in this work will consist in a test of the efficiency of this filter: first by simulating a link of 600 meters with three loops (one at the entry, one at the exit, and one at the 2/3 of the link), limiting the speed to 36 km/h and the flow to 1008 veh/h (calculation based on the fundamental diagram in the center of Nantes Metropole) with three scenarios (flow equal to 500 veh/h, 900 veh/h, and 2000 veh/h) such that 10% of the vehicles are considered as probe vehicles. Each scenario is simulated 100 times using the simulation software "AIMSUM". Second we will test this filter through an experiment with real data. Furthermore this method will be extended in order to be applied to a network with several lanes and crossroads. In addition, we will discuss the minimum number of probe vehicles required for a relevant estimation.

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